Analytical Optimal Solution of Selfish Node Detection with 2-hop Constraints in OppNets: A Pontryagin's Maximum Principle Approach

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***Abstract*—Selfish node detection offers an effective means to mitigate the routing performance degradation caused by selfish behaviors in Opportunistic Networks (OppNets), but leads to the extra network overload and computation cost. Most existing effort in the literature focuses on exploring the detection methods based on the traffic analysis or the cooperations among nodes. In this paper, we investigate the state transition of nodes in the message dissemination without detection. Specifically, the Ordinary Differential Equation (ODE) is constructed to approximatively model the periodic detection with complete detection requirement. Then we propose the optimal detection solution with the Pontryagin's maximum principle, and mathematically deduce the right detection time during the message lifetime. The model soundness is verified statistically and the analysis accuracy is evaluated via extensive simulations. The experiments also show that our solution can achieve the tradeoff between the reward and the detection cost.**

***Index Terms*—Selfish Node Detection, Ordinary Differential Equation, Pontryagin's Maximum Principle**

I. Introduction

Opportunistic networks (OppNets) have been proposed in the recent years, and are usually exploited to provide the network/communication service in the remote areas or the emergency situations. At present, with a widespread use and availability of mobile communication devices, OppNets presents very broad development prospect, and numerous applications rely on it prospered. [1] builded a cloud-based recommendation system OmniSuggest based on opportunistic mobile social network. In this project, user activities, mobility patterns are tracked to generate optimal venue recommendations. The opportunistic computing technology utilize the shared resources of OppNets to provide a platform for the execution of distributed computing tasks [2]. More examples can be found in mobile data offloading, such as [3], [4].

Exploiting mobile nodes to transmit message in OppNets has been attracting increasing research attentions [5]–[8]. Traditional message dissemination approaches heavily rely on voluntary cooperation between mobile nodes, which excessively consumes the limited energy supply and lead to massive useless message copies due to the selfish behavior. Adopting selfish node detection mechanisms to avoid selfish nodes involved in data forwarding, reduces and balances the communication loads of nodes (and thus their energy consumptions).

Much research effort on selfish node detection exists in the literature. The state-of-the-art detection schemes can be divided into two categories in light of their aims: watchdog systems [9]–[12] and social trust-based communications [13]–[15]. The former intends to detect selfish behavior by analyzing the traffic received from their encountered nodes while the latter establishes social trust relationships to select trusted and secured relay nodes. Most of the state-of-the-art work, either watchdog system methods or social trust-based communicating approaches, are micro-perspective studies, lead to network management cost due to the detecting expense, and introduce extra detection traffic, degrading the overall performance of OppNets.

Incentive methods, i.e., reward, are often exploited to attract the cooperations of nodes. But the selfish nodes can pretend to carry the message and gain the reward by cheating at the same time. The detection can decrease the impact of selfish behaviors effectively. However, the detection also introduces the detection cost, including the computation cost and the communication cost. In this paper, we exploit the Pontryagin's maximum principle to minimize the weighted cost of the detection and the reward based on the constructed message dissemination model. The main contributions are as follows.

- we formulate the ordinary differential equation model (ODE) to capture and analytically evaluate the state transition of nodes in OppNets without detection and with complete detection.
- we propose an optimal solution of selfish node detection based on the Pontryagin's maximum principle to achieve the tradeoff between the detection cost and the reward of selfish behaviors.
- we conduct experiments to evaluate the effectiveness of the proposed model and the optimal selfish detection solution in terms of the total cost, the wasted reward and the node state transition.

The rest of this paper is organized as follows. The literature is reviewed in Section II. We formulate the problem in Section III. The change of network state without detection and with fully detection is investigated in Section IV. The optimal solution of the selfish detection in OppNets is presented in Section V, and evaluated in Section VI. The paper concludes in Section VII.

II. Related Work

OppNets, which face two challenges, i.e., energy efficiency and network management cost minimization, are expected to accommodate participants with low-delay and cost-effective services. Therefore, many research works targeted to address these issues.

A. Message Transmission in OppNets

In order to mitigate the performance degradation caused by the selfish behaviors in OppNets, much effort has been made to explore the methods of selfish node detection [7], [16]. An early investigation on the selfish behavior detection is [9], where the watchdog nodes were proposed to analyze the traffic received from their encountered nodes. This work was extended for applications with the elimination of the limited knowledge on node detection by single watchdog, and the cooperative systems with multiple watchdogs were proposed in [10]–[12]. [10] proposed a collaborative approach (CoCoWa, Collaborative Contact-based Watchdog), which considered the diffusion of local selfish nodes awareness, to conduct the selfish node detection in MANETs. Through accelerating the information propagation, the method improved the performance of selfish node detection in terms of the time and the precision. [12] proposed a social-based watchdog system (SoWatch), with a watchdog module to protect SoWatch against the wrong watchdogs manipulated by malicious nodes.

Another kind of approach tries to establish social trust relationships between mobile nodes in OppNets by leveraging their online social information (explicit trust) as well as their interactions or mobility properties (implicit trust). In [13], a probabilistic misbehavior detection scheme(iTrust), which introduced a periodically available Trusted Authority(TA), was presented to judge a node's behavior. Another trust framework PROVEST (PROVEnance-baSed Trust model) that aimed to achieve accurate peer-to-peer trust assessment was presented in [14]. The partial selfishness was investigated and credit-based algorithm to measure the degree of selfishness was designed in [15].

[17] combined watchdog technique with trust-based communications and integrated with PRoPHET to build a global perception of forwarding behavior for detection of selfish nodes. [18] introduced ensemble learning for environment-adaptive malicious node detection. [19] integrated buffer-aided full-duplex/half-duplex relaying with non-orthogonal multiple access(BAHyNOMA) for relay selection.

Routing is a critical bottleneck when selfish behavior is exhibited and a potential alleviation is to develop incentivizing mechanisms for message forwarding. Incentive-based protocols, such as SEIR [20], Multicent [21], were devised to increase node participation in message forwarding by opting for mechanisms that reward active participation of nodes in the forwarding of messages and penalize them otherwise. To balance the tradeoff between the delivery rate and forwarding cost, game theory was introduced to optimize the configuration in MANET for more efficient energy-aware routing in [22]. While geo-casting routing protocols like LoSeRo [23] exploited the location data to enhance the message routing performance, onion-based anonymous routing approach [24] and ePRIVO [25] were proposed to keep users' information private. For MOSNs, which exhibits a nested core-periphery hierarchy(NCPH), [26] presented an up-and down routing protocol to upload message from source node to the network core and then download to the destination. [27] proposed a context-aware self-adaptive routing protocol that is able to adapt to different scenarios.

B. Optimizations of OppNets

Optimization schemes of OppNets can be classified into several types, the most typical one tries to formulate the transmitting process in terms of a trade-off between the network management cost and the transmission performance. For example, on optimal neighbor discovery, PWEND [28] and Pharos [29] adopted time model for neighbor discovery and investigated the most energy efficient way and the least discovery latency, respectively. Then for a given energy budget, how to optimizing the number of discovered peers was researched in [8], what is the best achievable discovery latency was addressed by [30].

As for optimal data forwarding, [31] proposed an efficient time-aware data forwarding strategy(TCCB) for OMNs, based on temporal social contact patterns. The model performed a close delivery ratio to Epidemic but with significantly reduced delivery cost. [32] introduced a centralized heuristic algorithm which aimed to discover a tree for multicasting, with resource constrained (e.g. the delay-constrained least-const) in MONs. Both centralized and decentralized single-copy message forwarding algorithms were proposed in [33], which aimed to minimize the expected latencies from any node in the Opportunistic DTNs. However, aforementioned works just consider one part of the message transmission in OppNets, [34] mathematically characterized message transmission of the selfish and altruistic cases as an optimal control problem, whose controlling parameters were chosen according to the forwarding rate and beaconing rate, respectively. Then the Pontryagin's Maximum Principle was exploited to search the problem solution in multiple destinations scenario and the optimal control policies were proved to satisfy the threshold form.

Minimize the contact duration by optimizing mobile data offloading in OMNs is the objective of [35], [36]. A mathematical framework to study the problem of coding-based mobile data offloading was established in [35], the authors formulated the problem as a users' interest satisfaction maximization problem with multiple linear constraints of limited storage and efficient scheme was proposed to solve it. An optimal traffic offloading scheme through data partition, which generated forwarding paths with possible heterogeneous data chunks, was presented in [36].

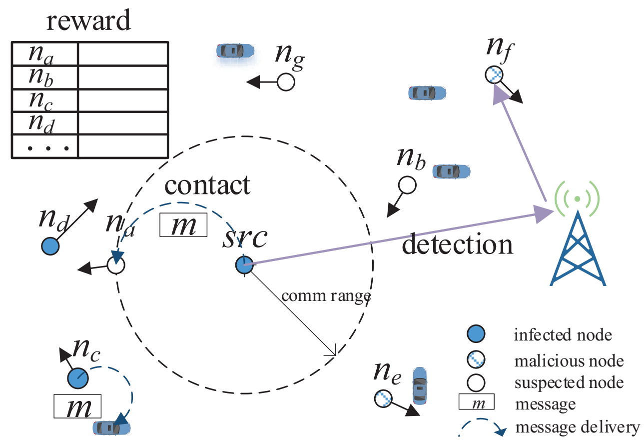

Fig. 1. Reward and Detection of the selfish nodes in OppNets.

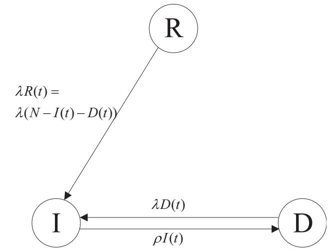

Fig. 2. State transition of the relay nodes without detection.

Few these existing works focus on optimal control policy, while we introduce it for selfish node detection, where the scenario is different from [34] in this paper.

III. Preliminaries

The source node src needs to disseminate its message m to vehicles or pedestrians, where the lifetime of m is T. There are N relay nodes that can receive m and broadcast m, which is shown in Fig. 1. Thus the potential coverage area of m is broadened by the opportunistic network. src usually reward the relay node n_i $(1 \leq i \leq N)$ for its collaboration, where the reward can be quantifies as the message carrying time. However, n_i may discard m immediately after the contact to earn the reward without carrying m, which is the selfish behavior. For example, when the contact between src and n_i occurs, m is replicated n_i at time τ_0, which is recorded by src. If n_i carries m until the lifetime T, the reward, which is proportional to $T - \tau_0$, will be offered to n_i for its contribution. But if n_i discards m at time τ_1, $\tau_0 < \tau_1 < T$, a part of reward, $T - \tau_1$, is wasted because src can not obtain τ_1.

To decrease the wasted reward, src can conduct the selfish node detection, whose process are as follows. 1) src first randomly select the target relay node n_i and the message segment L. 2) src send the query of L's checksum to n_i via the wireless communication, e.g., the cellular network. 3) If the check of n_i failed, n_i would not receive the reward from the detection time. Note that the minimum cycle of a detection process is T_m, which is constrained by the computation of checksum and the communication of querying. In this paper, we will propose the optimal selfish node detection strategy to achieve the tradeoff between the detection cost and the wasted reward by selfish behaviors.

$R(t)$ denotes the expected number of the relay nodes, which have not contacted src before time t. $I(t)$ denotes the expected number of infected relay nodes, which still carry m at time t. $D(t)$ denotes the expected number of selfish relay nodes, which have discarded m but are not known by src at time t. Similar to [37] and [38], the contacts between src and every relay node are assumed to occur according to the Poisson process, where the contact rate is λ. The total number of relay nodes is N. So $N = R(t) + I(t) + D(t)$, $\forall t$, $0 \leq t \leq T$. We assume the rate of change from state I to state D is a constant value ρ. The detection rate is $U(t)$, $0 \leq U(t) \leq U_m$. which can be controlled by src. For example, if the minimum detection cycle T_m is 0.5 seconds, the maximum detection rate is that $U_m = \frac{1}{T_m} = 2$ times per second. Then the main objective of our work is to to solve the following problem,

$$Min : J = \int_0^T (1-\alpha)D(t) + \alpha U(t) dt, \tag{1}$$

where α is the constant weight, $0 \leq \alpha \leq 1$. This objective will minimize the reward, which is paid to the selfish nodes in state D and the detection cost. Additionally, the total paid reward is,

$$P = \int_0^T \beta(I(t) + D(t))dt, \tag{2}$$

where β is the reward paid for a node's contribution in a second. In order to realize our proposed detection, we also should ensure P is limited in OppNet.

IV. Message Dissemination Model

We investigate the selfish detection in this and the following sections. Specifically, in this section, the ordinary differential equation model is constructed to capture the state transition and the message dissemination without detection and with complete detection.

A. Case 1: without detection

In the case without detection, the relay node with message can become the selfish node, but the selfish detection is not conducted by src. Then the state transition is shown in Fig. 2 with the following rules. The nodes change from state R to state I if they contact src. The corresponding incremental rate of state I is $\lambda R(t)$ at time t. Since the selfish node may also contact src with the contact rate λ, the rate of change from state D to state I is $\lambda D(t)$. Because $N = R(t) + I(t) + D(t)$, the total incremental rate of $I(t)$ is $\lambda(R(t) + D(t)) = \lambda(N - I(t))$. Additionally, the rate of change from state I to state D is $\rho I(t)$. We can obtain the derivative of $I(t)$ with respect to time t, $\frac{\mathrm{d}I(t)}{\mathrm{d}t} = \lambda(N - I(t)) - \rho I(t)$. Similar to $\frac{\mathrm{d}I(t)}{\mathrm{d}t}$, we can get the derivative of $D(t)$ and the derivative of $R(t)$ respectively, i.e., $\frac{\mathrm{d}D(t)}{\mathrm{d}t}$ and $\frac{\mathrm{d}R(t)}{\mathrm{d}t}$. Thus the state transition can be represented as

$$\begin{aligned}
\frac{\mathrm{d}I(t)}{\mathrm{d}t} &= \lambda(N - I(t)) - \rho I(t), \\
\frac{\mathrm{d}D(t)}{\mathrm{d}t} &= -\lambda D(t) + \rho I(t), \\
\frac{\mathrm{d}R(t)}{\mathrm{d}t} &= -\lambda(N - I(t) - D(t)).
\end{aligned} \tag{3}$$

Since $I(t)$ in (3) is formed by the first-order first-power ordinary differential equations (ODE) [38], we can obtain the general solutions of $I(t)$, that is,

$$I(t) = C_I e^{-(\lambda+\rho)t} + \frac{\lambda N}{\lambda+\rho}.$$

Note that $I(0) = 0$, $D(0) = 0$ and $R(0) = N$, which means only src carries the message at time 0. Thus $C_I = \frac{-\lambda N}{\lambda+\rho}$, and

$$I(t) = \frac{\lambda N}{\lambda+\rho}(1 - e^{-(\lambda+\rho)t}),$$

where $0 \le t \le T$. Similarly, we can calculate the general solution of the first-order ODE $D(t)$ from $\frac{\mathrm{d}D(t)}{\mathrm{d}t} + \lambda D(t) = \rho I(t)$,

$$\begin{aligned} D(t) &= C_D e^{-\int \lambda dt} + e^{-\int \lambda dt} \int \rho I(t) e^{\int \lambda dt} dt \\ &= C_D e^{-\lambda t} + \frac{\lambda N}{\lambda+\rho} e^{-(\lambda+\rho)t} + \frac{\rho N}{\lambda+\rho}. \end{aligned} \tag{4}$$

Because of $D(0) = 0$,

$$D(t) = -N e^{-\lambda t} + \frac{\lambda N}{\lambda+\rho} e^{-(\lambda+\rho)t} + \frac{\rho N}{\lambda+\rho}.$$

Since $I(t) + D(t) + R(t) = N$, $0 \le t \le T$, $R(t)$ can be computed based on the solved solution of $I(t)$ and $D(t)$. Thus the solution of (3) can be derived as

$$\begin{aligned} I(t) &= \frac{\lambda N}{\lambda+\rho}(1 - e^{-(\lambda+\rho)t}), \\ D(t) &= N(\frac{\lambda e^{-(\lambda+\rho)t} + \rho}{\lambda+\rho} - e^{-\lambda t}), \\ R(t) &= N e^{-\lambda t}, \end{aligned} \tag{5}$$

which depicts the change of the states when the time ranges from 0 to T. And $I(t)$, $D(t)$, $R(t) \ge 0$ always hold when $t \ge 0$. From the solutions of $I(t)$, $D(t)$ and $R(t)$, we can find that $I(t) \to \frac{\lambda N}{\lambda+\rho}$, $D(t) \to \frac{\rho N}{\lambda+\rho}$ and $R(t) \to 0$, when $t \to +\infty$. To verify the validity of the ODE model (3), we conduct the simulations with randomly settings. The corresponding results are presented in Section. VI-A.

The cost J in (1) also can be calculated based on (5). Note that $U(t) = 0$, $\forall t$, in the case without detection. J is determined by the expected number of selfish nodes $D(t)$, $0 \le t \le T$, which is proportional to the reward consumed by selfish behaviors. Thus J can be computed as

$$\begin{aligned} J &= \int_0^T (1-\alpha) D(t) dt, \\ &= \int_0^T (1-\alpha) N(\frac{\lambda e^{-(\lambda+\rho)t} + \rho}{\lambda+\rho} - e^{-\lambda t}) dt, \\ &= N(1-\alpha)\left(\frac{\lambda(1 - e^{-(\lambda+\rho)T})}{(\lambda+\rho)^2} + \frac{\rho T}{\lambda+\rho} - \frac{1 - e^{-\lambda T}}{\lambda}\right). \end{aligned} \tag{6}$$

Similarly, we can get the total paid reward in this case

$$P = \beta \int_0^T I(t) + D(t) dt = N\beta(T - \frac{1 - e^{-\lambda T}}{\lambda}).$$

Furthermore, the fraction between the wasted reward and the total paid reward can be obtained as

$$p = \frac{\int_0^T D(t) dt}{\int_0^T I(t) + D(t) dt} = \frac{\frac{\lambda(1-e^{-(\lambda+\rho)T})}{(\lambda+\rho)^2} + \frac{\rho T}{\lambda+\rho} - \frac{1-e^{-\lambda T}}{\lambda}}{T - \frac{1-e^{-\lambda T}}{\lambda}}.$$

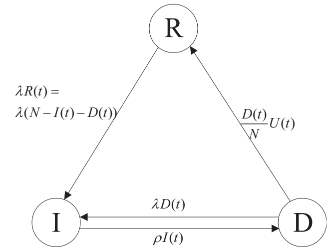

Fig. 3. State transition of the relay nodes.

B. Case 2: with complete detection

In the case with complete detection, src conducts the selfish node detection in the whole message lifetime. The detections are conducted at time $T_m, 2T_m, \cdots, kT_m$, where $kT_m \le T < (k+1)T_m$. In every detection, a randomly selected node n_i is checked by src whether n_i is a selfish node. We can find that the decrement of selfish node number only occurs at the instant iT_m in the case with complete detection.

In order to simplify the model, we exploit a continuous manner to describe this case with complete detection. Considering that the checked relay node is randomly selected from the N node set, we calculate the probability of selecting a selfish node as $\frac{D(t)}{N}$. Since the detection rate is constrained by $U(t)$, we let $\frac{D(t)}{N}U(t)$ denote the change rate from state D to state R caused by detections. Thus the state transition of the fully detection case is constructed as Fig. 3. The approximate model of the state transition in the case with complete detection will be constructed as

$$\begin{aligned} \frac{\mathrm{d}I(t)}{\mathrm{d}t} &= \lambda(N - I(t)) - \rho I(t), \\ \frac{\mathrm{d}D(t)}{\mathrm{d}t} &= -\lambda D(t) + \rho I(t) - \frac{D(t)}{N}U(t), \\ \frac{\mathrm{d}R(t)}{\mathrm{d}t} &= -\lambda(N - I(t) - D(t)) + \frac{D(t)}{N}U(t), \end{aligned} \tag{7}$$

based on the model in the case without detection (3). Here $U(t) = U_m$, $\forall t$, $0 \le t \le T$. The initial state is that $I(0) = D(0) = 0$ and $R(0) = N$. So the solution of $I(t)$, which does not change from (5), is that $I(t) = \frac{\lambda N}{\lambda+\rho}(1 - e^{-(\lambda+\rho)t})$. From $\frac{\mathrm{d}D(t)}{\mathrm{d}t} + (\lambda + \frac{U_m}{N})D(t) = \rho I(t)$, we can derive that

$$\begin{aligned} &D(t) \\ =&C_{2D} e^{\int -(\lambda + \frac{U_m}{N})dt} + e^{\int -(\lambda + \frac{U_m}{N})dt} \int \rho I(t) e^{\int (\lambda + \frac{U_m}{N})dt} dt \\ =&C_{2D} e^{-(\lambda + \frac{U_m}{N})t} - \frac{\rho\lambda N}{(\lambda+\rho)(\frac{U_m}{N} - \rho)} e^{-(\lambda+\rho)t} + \frac{\rho\lambda N}{(\lambda+\rho)(\lambda + \frac{U_m}{N})}. \end{aligned}$$

Since $D(0) = 0$ and $I(t) + D(t) + R(t) = N$, the solution of (7) can be calculated as

$$\begin{aligned}
I(t) =&\frac{\lambda N}{\lambda+\rho}(1-e^{-(\lambda+\rho)t}),\\
D(t) =&\frac{\rho\lambda N}{(\lambda+\rho)(\lambda+\frac{U_m}{N})}+\frac{\rho\lambda N}{(\lambda+\frac{U_m}{N})(\frac{U_m}{N}-\rho)}e^{-(\lambda+\frac{U_m}{N})t}\\
&-\frac{\rho\lambda N}{(\lambda+\rho)(\frac{U_m}{N}-\rho)}e^{-(\lambda+\rho)t},\\
R(t) =&N-\frac{\lambda N}{\lambda+\rho}\left(\frac{\rho}{\lambda+\frac{U_m}{N}}+1\right)+\frac{\lambda U_m}{(\lambda+\rho)(\frac{U_m}{N}-\rho)}e^{-(\lambda+\rho)t}\\
&-\frac{\rho\lambda N}{(\lambda+\frac{U_m}{N})(\frac{U_m}{N}-\rho)}e^{-(\lambda+\frac{U_m}{N})t}.
\end{aligned} \tag{8}$$

We can find that $I(t)\to\frac{\lambda N}{\lambda+\rho}$, $D(t)\to\frac{\rho\lambda N}{(\lambda+\rho)(\lambda+\frac{U_m}{N})}$, and $R(t)\to N-\frac{\lambda N}{\lambda+\rho}\left(\frac{\rho}{\lambda+\frac{U_m}{N}}+1\right)$ when $t\to+\infty$ according to (8). Here $R(+\infty)\neq 0$ in the steady state is caused by the complete selfish detection. Based on the approximate model (7) and the corresponding solutions (8), the estimation of the total cost $\hat{J}$ can be computed as

$$\begin{aligned}
\hat{J} =&\int_0^T (1-\alpha)D(t)+\alpha U(t)dt,\\
=&\frac{(1-\alpha)\rho\lambda NT}{(\lambda+\rho)(\lambda+\frac{U_m}{N})}-\frac{(1-\alpha)\rho\lambda N}{(\lambda+\frac{U_m}{N})^2(\frac{U_m}{N}-\rho)}(e^{-(\lambda+\frac{U_m}{N})T}-1)\\
&+\frac{(1-\alpha)\rho\lambda N}{(\lambda+\rho)^2(\frac{U_m}{N}-\rho)}(e^{-(\lambda+\rho)T}-1)+\alpha TU_m.
\end{aligned} \tag{9}$$

The reason why (9) is the estimation of the cost is that the decrement of $D(t)$ actually occurs in the end of the detection cycle. However, the change rate of $D(t)$ in (7) is denoted by $\frac{D(t)}{N}U(t)$ in the above analysis. So there exists a deviation between the true cost J and the estimated cost $\hat{J}$ in the case with complete detection.

Lemma 1. *When $t\to+\infty$, $T_m\ll T$, a deviation between $D(t)$ in the approximate model (8) and in the real scenario is limited.*

Proof. At first we discuss the real scenario of the complete detection case. Without loss of generality, assume that $(0,T)$ can be divided into k detection cycles and a following duration t_{k+1}. Here the i-th detection cycle is denoted by $(t_{i-1},t_i]$, where $t_i-t_{i-1}=T_m$ and $t_{k+1}<T_m$. In every detection cycle, $D(t)$ increases from $D(t_{i-1})$ to $D(t_i^-)$ in (t_0,t_1^-). Since the detection occurs at the instant t_i, $D(t_i^+)=\frac{N-1}{N}D(t_i^-)$. From (5) we can find that $D(t)$ increases with time in the case and approaches to the stable state in the case without detection. In the case with complete detection, when $t\to+\infty$, $D(t)$ also approaches to the stable state, where $D(t_{i-1}^+)=D(t_i^+)$. We can obtain that

$$\begin{aligned}
D(t_{i-1}^+) =&C_i e^{-\lambda t_{i-1}^+}+\frac{\lambda N}{\lambda+\rho}e^{-(\lambda+\rho)t_{i-1}^+}+\frac{\rho N}{\lambda+\rho},\\
D(t_i^-) =&C_i e^{-\lambda t_i^+}+\frac{\lambda N}{\lambda+\rho}e^{-(\lambda+\rho)t_i^+}+\frac{\rho N}{\lambda+\rho},
\end{aligned}$$

in (t_{i-1},t_i) based on (4). Then, when $i\to+\infty$,

$$\begin{aligned}
D(t_i^+) =&\frac{N-1}{N}D(t_i^-)\\
=&\frac{N-1}{N}D(t_{i-1}^+)e^{-\lambda T_m}+\frac{\rho(N-1)}{\lambda+\rho}(1-e^{-\lambda T_m})
\end{aligned}$$

Considering that $D(t_{i-1}^+)=D(t_i^+)$, we can get that

$$\begin{aligned}
\lim_{i\to+\infty}D(t_i^+) =\frac{\rho(N-1)}{\lambda+\rho}\frac{1-e^{-\lambda T_m}}{(1-\frac{N-1}{N}e^{-\lambda T_m})}\\
\lim_{i\to+\infty}D(t_i^-) =\frac{\rho N}{\lambda+\rho}\frac{1-e^{-\lambda T_m}}{(1-\frac{N-1}{N}e^{-\lambda T_m})}
\end{aligned}$$

According to (8), $D(+\infty)=\frac{\rho\lambda N}{(\lambda+\rho)(\lambda+\frac{U_m}{N})}$. Since these limitations are the limited values related to ρ, λ, N and U_m, the deviation of $D(t)$ between in the approximate model and in the real scenario is limited. □

Lemma 2. *Let J denote the cost in the complete detection case. In the case with fully detection, $|J-\hat{J}|$ is less than $(1-\alpha)TN$.*

Proof. Considering that $U(t)=\hat{U}(t)=U_m$, we can derive that $\int_0^T U(t)dt=TU_m=\int_0^T\hat{U}(t)dt$. And the deviation between the estimated cost and the true cost

$$\begin{aligned}
|J-\hat{J}| =&\left|\int_0^T(1-\alpha)D(t)dt-\int_0^T(1-\alpha)D\hat{(}t)dt\right|\\
\le&(1-\alpha)\int_0^T|(D(t)-D\hat{(}t))|dt\\
\le&(1-\alpha)TN
\end{aligned} \tag{10}$$

where $0\le D(t),D\hat{(}t)\le N$.

□

We also can compute the approximate total reward is

$$\begin{aligned}
\hat{P} =&\beta\int_0^T I(t)+D(t)dt,\\
=&\frac{\beta\rho\lambda NT}{(\lambda+\rho)(\lambda+\frac{U_m}{N})}-\frac{\beta\rho\lambda N}{(\lambda+\frac{U_m}{N})^2(\frac{U_m}{N}-\rho)}(e^{-(\lambda+\frac{U_m}{N})T}-1)\\
&+\frac{\beta\rho\lambda N}{(\lambda+\rho)^2(\frac{U_m}{N}-\rho)}(e^{-(\lambda+\rho)T}-1)+\frac{\lambda N}{(\lambda+\rho)^2}(e^{-(\lambda+\rho)T}-1)\\
&+\frac{\beta\lambda NT}{\lambda+\rho}
\end{aligned}$$

Similarly, the utilization ratio of reward also can be obtained $\hat{p}=\frac{\int_0^T D(t)dt}{\int_0^T I(t)+D(t)dt}$. From (8) to (5), we find $I(t)$ does not change but $D(t)$ decreases. Thus this complete detection case can reduce the selfish behaviors with the additional cost of the selfish node detections, e.g., energy, bandwidth and wireless communication fee. Thus we try to achieve the tradeoff between the paid reward and the detection cost via the optimal solution.

V. Optimal Detection

A. Problem Formulation

Assume that the detection can be conducted. The detection rate is $U(t)$, $0\le U(t)\le U_m$. U_m is the limitation of the detection rate, which is the constraint from the hardware and the time sequences. Then, the ODEs can be reformulated as

$$\begin{aligned}
\frac{\mathrm{d}I(t)}{\mathrm{d}t}&=\lambda(N-I(t))-\rho I(t),\\
\frac{\mathrm{d}D(t)}{\mathrm{d}t}&=\rho I(t)-\lambda D(t)-\frac{D(t)}{N}U(t),\\
\frac{\mathrm{d}R(t)}{\mathrm{d}t}&=-\beta(N-I(t)-D(t))+\frac{D(t)}{N}U(t).
\end{aligned} \tag{11}$$

Meanwhile,

$$\begin{aligned} I(0) &= 0, \\ D(0) &= 0, \\ R(0) &= N. \end{aligned} \tag{12}$$

Thus $I(t)$ is the same with that in the situation without detection, which is

$$I(t) = \frac{\lambda N}{\lambda + \rho}(1 - e^{-(\lambda+\rho)t}). \tag{13}$$

Considering that the detection is also the cost, the object function will be

$$J = \int_0^T (1-\alpha)D + \alpha U dt.$$

Here α is the weight, which can control the importance between the cost of selfish relay nodes and detections. Thus $0 < \alpha < 1$. Similar with the previous section, $I(t)$ and $D(t)$ is the state functions. $U(t)$ is the controllable variable, $0 \leq U(t) \ \leq U_m$.

B. Optimal Control by Pontryagin's Maximum Principle

Now we utilize the Pontryagin's maximal principle [34] to find the optimal $U(t)$, which will minimize the total cost. First, the Hamilton function is

$$\begin{aligned} H =& (1-\alpha)D + \alpha U + \lambda_I(\lambda(N-I) - \rho I) \\ &+ \lambda_D(\rho I - \lambda D - \frac{D}{N}U) \\ =& (1-\alpha)D + \lambda_I(\lambda(N-I) - \rho I) \\ &+ \lambda_D(\rho I - \lambda D) + (\alpha - \lambda_D \frac{D}{N})U. \end{aligned}$$

Note that λ_I and λ_D denote two co-state functions. Without the final constraint, the terminal condition is $\lambda_I(T) = 0$ and $\lambda_D(T) = 0$. Then the adjoint function is

$$\dot{\lambda_D} = -\frac{\partial H}{\partial D} = \lambda_D(\lambda + \frac{U}{N}) - (1-\alpha).$$

Thus

$$U^*(t) = \begin{cases} 0, & \text{if } \alpha - \lambda_D \frac{D}{N} \geq 0 \\ U_m, & \text{if } \alpha - \lambda_D \frac{D}{N} < 0 \end{cases} \tag{14}$$

In summary, we have the ODE functions $\dot{D}$, $\dot{\lambda_2}$, the initial condition $D(0) = 0$ and the boundary condition $\lambda_D(T) = 0$, Thus the problem is to solve a BVP problem, which is

$$\begin{aligned} \dot{D} &= -(\lambda + \frac{U^*}{N})D + \rho I, \\ \dot{\lambda_2} &= (\lambda + \frac{U^*}{N})\lambda_D - (1-\alpha), \end{aligned} \tag{15}$$

where $D(0) = 0$ and $\lambda_D(T) = 0$. We can solve the BVP problem with the shooting method by the bvpSolve package of R. The whole algorithm are shown in Alg. 1, where δt presents the time granularity. The message replication time τ_0 and the state switching time are recorded by src. So the reward can also be computed by src. Then we analyze the properties of the optimal control variable.

Algorithm 1 Optimal Selfish Node Detection

Require: T_m, U_m, λ, ρ, T
time $t \leftarrow 0$
compute the solution of (15) as the switch-on duration $\mathcal{T}$
while $t \leq T$ **do**
  if contact n_i without message **then**
    replicate m to n_i
    state of n_i changes to I
    record t as τ_0
  end if
  if $t \in \mathcal{T}$ **then**
    select a relay node n_j randomly
    conduct the detection of n_j
    if n_j is detected as a selfish node **then**
      state of n_j changes to R
      record t as the state switch time
    end if
  end if
  $t \leftarrow t + \delta t$
end while
for n_i, $1 \leq i \leq N$ **do**
  pay the reward to n_i based on the time of staying state I
end for

Lemma 3. *At the beginning and the end of the whole duration, the optimal control stop the selfish detection, which is $U(0) = U(T) = 0$.*

Proof. At the beginning of the duration, $M(0) = 0$, which is the initial condition of 15. Then $\alpha - \lambda_2(0)\frac{M(0)}{N} = \alpha > 0$. Following (14), the optimal $U(0) = 0$.

At the end of the duration, $\lambda_2(T) = 0$, which is the boundary condition of 15. Then $\alpha - \lambda_2(T)\frac{M(T)}{N} = \alpha > 0$. Based on (14), the optimal $U(T) = 0$. ☐

Based on the differential function $\dot{I}$, the equilibrium point of I can be obtained from $\dot{I} = 0$, which is $I^* = \frac{\beta N}{\beta + \rho}$. When $I(t) < I^*$, $I(t)$ will increase with t and approach to $\frac{\beta N}{\beta + \rho}$. Meanwhile, in this paper $I(0) = 0$ at the beginning of time.

Based on the differential function $\dot{M}$, the equilibrium point is obtained from $\dot{M} = 0$, which is $M^* = \frac{\rho I}{\beta + \frac{1}{N}U}$. In the situation without detection, the equilibrium point is $M^* = \frac{\rho I^*}{\beta} = \frac{\rho N}{\beta + \rho}$. In the situation with full detection, the equilibrium point is $M^* = \frac{\rho I^*}{\beta + \frac{1}{N}U_m} = \frac{\rho}{\beta + \frac{1}{N}U_m}\frac{\beta N}{\beta + \rho}$.

Since α is the weight of detecting the selfish nodes, we can assume that if α is enough high, the detection will not perform according to the optimal control strategy.

Lemma 4. *If $\alpha \geq \alpha_{th}$, the optimal control let the detection stop in the whole duration, namely $U(t) = 0$, $0 \leq t \leq T$.*

Proof. Assume that ρ, N, β is given. Let $W(t) = \lambda_2(t)M(t)$.

$$\begin{aligned} W^{'}(t) =& M^{'}(t)\lambda_2(t) + M(t)\lambda_2^{'}(t) \\ =& (\rho I(t) - \beta M(t) - \frac{M(t)}{N}U(t))\lambda_2(t) \\ &+ M(t)(\lambda_2(t)(\beta + \frac{U(t)}{N}) - (1-\alpha)) \\ =& \rho\lambda_2(t)I(t) - (1-\alpha)M(t). \end{aligned} \tag{16}$$

Since $M(0) = 0$ and $\lambda_2(T) = 0$, $W(0) = W(T) = 0 < \alpha N$.

Now we focus on the poles of $W(t)$, namely t^*, where $W^{'}(t^*) = \rho\lambda_2(t^*)I(t^*) - (1-\alpha)M(t^*) = 0$. Then $M(t^*) = \frac{\rho\lambda_2(t^*)I(t^*)}{1-\alpha}$.

$$W(t^*) = \lambda_2(t^*)M(t^*) = \frac{\rho I(t^*)\lambda_2(t^*)^2}{1-\alpha}. \quad (17)$$

According to $\dot{\lambda_2}$ in (15), the equilibrium point of λ_2 is that $\lambda_2^* = \frac{1-\alpha}{\beta+\frac{U}{N}}$. Since $0 \le U \le U_m$, $0 < \frac{1-\alpha}{\beta+\frac{U_m}{N}} \le \lambda_2^* \le \frac{1-\alpha}{\beta}$. Note $\lambda_2(T) = 0$. Based on the phase line in ODE for $\dot{\lambda_2}$, $\lambda_2(t)$ decreases with t when $\lambda_2(t) < \lambda_2^*$. Conversely, $\lambda_2(t)$ increases with t when $\lambda_2(t) > \lambda_2^*$. Thus $0 \le \lambda_2(t) \le \lambda_2^* \le \frac{1-\alpha}{\beta}$ when $0 \le t \le T$. Additionally, $0 \le I(t) \le \frac{\beta N}{\beta+\rho}$. From (17), we can derive that the upper boundary of $W(t)$, W_{up}, which is

$$W(t) \le W(t^*) \le \frac{\rho}{1-\alpha}\frac{\beta N}{\beta+\rho}(\frac{1-\alpha}{\beta})^2 = \frac{\rho N(1-\alpha)}{\beta(\beta+\rho)} = W_{up}.$$

Assume that α can satisfy that $W_{up} \le \alpha N$, which means that $\alpha \ge \frac{\rho}{\beta(\beta+\rho)+\rho} = \alpha_{th}$. Then $W(t) \le \alpha N$, when $0 \le t \le T$. Therefore the optimal control $U^*(t) \equiv 0$, when $0 \le t \le T$. □

VI. Performance Evaluation

We consider a $5000 \times 5000m^2$ sparse sensing field with 100 relay nodes. The Poisson-contact mobility model is quasi-synthetic, in which the parameter λ is set to 0.004. The source node is fixed at the center of the network scenario. The speed of nodes is randomly selected in a uniform distribution changing from 4 to 10 m/s, and the communication range of these nodes is set to be $20m$. The parameter α is limited, i.e., $\alpha \in [0, 1]$. We consider two cases in the simulations. In the first case (Section IV-A), we set $U(t) = 0$, which means there is no selfish detection. In the second case (Section IV-B), we adopt the selfish detection method and keep detecting during whole lifetime of network. In each simulation, M messages are created, whose maximal lifetime T_m increases from $0s$ to $2000s$. Note that, all statistical results of our scheme are obtained by repeating 50 times.

A. Accuracy Analysis Based on Simulations

As shown in Sections IV and V, we mathematically model the state transition of nodes by the ODEs, based on which we analyze the optimal control through the Pontryagin's Maximum Principle. It is critical to verity the accurate of the proposed model. Therefore, in the first experiment, we compare the the simulation and the analytical results to check the accuracy of models. Fig. 4 shows the comparison between the simulation and the analytical result in Case 1, in which $D(t)$, $I(t)$ and $R(t)$ with time t are computed from prediction and simulations when $\lambda = 0.004$, $\rho = 0.01$, $N = 100$ and $T = 2,500$, and the dotted lines represent the analytical results. As can be seen, the analytical results match the simulation results reasonably, which validates the proposed analytical model.

The result in Fig. 5 shows that the accuracy of the proposed ODE models in Case 2. In this figure, $I(t)$, $D(t)$ and $R(t)$ with

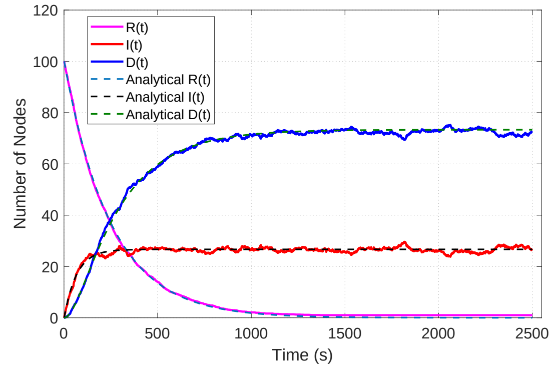

Fig. 4. Comparison of the theoretical and simulation results of the proposed ODE model in case 1.

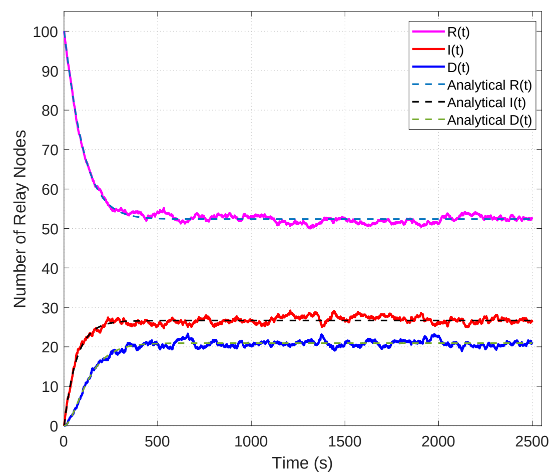

Fig. 5. Comparison of the theoretical an simulation results or the proposed ODE model in case 2.

time t are computed from prediction and simulations when $\lambda = 0.004$, $\rho = 0.011$, $N = 100$, $T_m = 1$ and $T = 2,500$. According to Equation (8), we can know that the analytical results about total number of $D(t)$ is in a monotone increasing situation when the growing T. The blue line in Fig. 5 proves this conclusion. However, the number of selfish number reduce to 20 when comparing with Fig. 4. This is because adopting detection methods will mitigate the selfish behaviour of nodes. Fig 5 verifies the accuracy of the proposed ODE model again.

B. Efficacy of the approximate method

In the second experiment, we analysis efficacy of the approximate method. Fig. 6 shows the state transition of nodes with time T, in which $M(t)$ represent , $I(t)$ represent , $S(t)$ represent and λ_2 represent. As we can see, the value of $M(t)$ and the value of λ_2 decrease with T. In contrast, both $S(t)$ and $I(t)$ have growing trend with increasing T. This verify the sate transition is balanced.

Fig. 7 shows the control variable $U(t)$ with increasing time. From this figure, we can easily obtain the optimal control

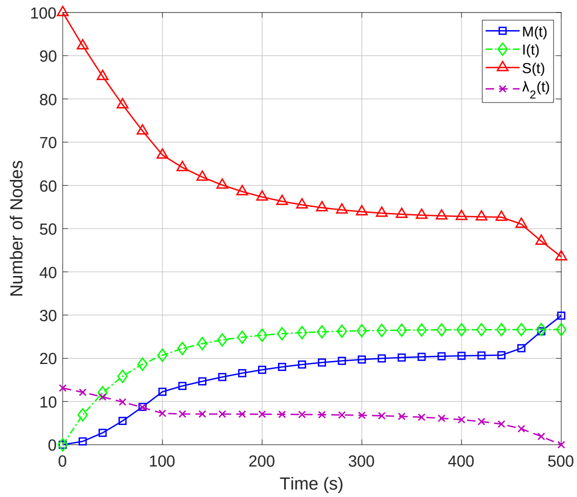

Fig. 6. State variable of analysis with time.

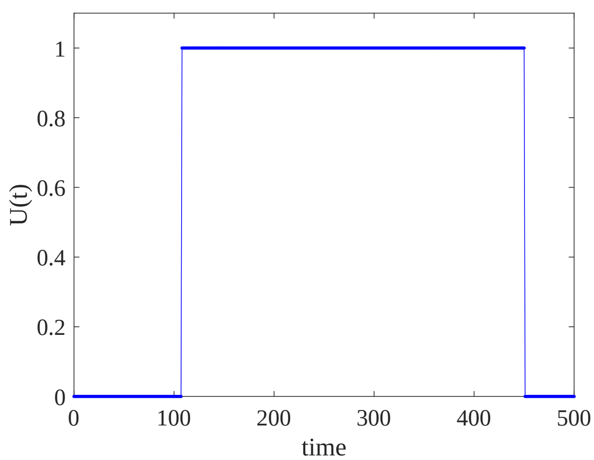

Fig. 7. The optimal control policy of $U(t)$.

policy to minimize the J. For example, when T equals to 100, the complete detection is open. When time equals to 450, the network will switch from an 'on state' to an 'off state'.

C. Optimal solution of selfish detection

In the third experiment, we analysis the impact of different t_0 and t_1.

VII. Conclusion

In this paper, we have analytically investigated the state transition of nodes in the opportunistic networks. The ordinary differential equation models have been constructed to capture the message dissemination with complete detection, which can suppress the increment of selfish node number. To achieve the tradeoff the reward and the detection cost in the message lifetime, we propose the optimal solution of the selfish node detection based on the Pontryagin's maximum principle. The soundness of the models and the accuracy of the analysis have been verified via extensive simulation.

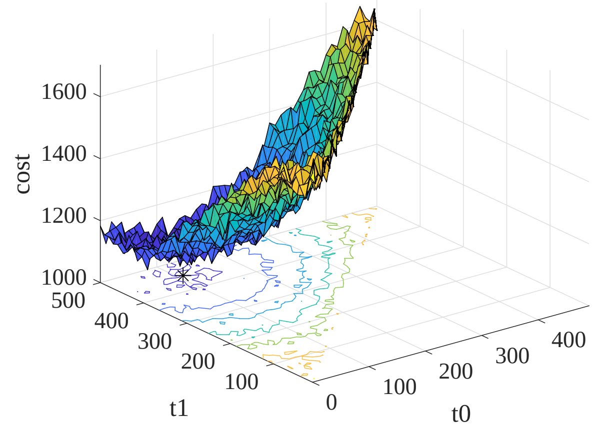

Fig. 8. Different choices of $t0$ and $t1$.

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